Barcelona Supercomputing Center
Centro Nacional de Supercomputación

A test-bed for joint climate prediction and services approach

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EXCELENCIA SEVERO OCHOA

What

Environmental forecasting

Why

Our strength …
- … research …
- … operations …
- … services …
- … high resolution …

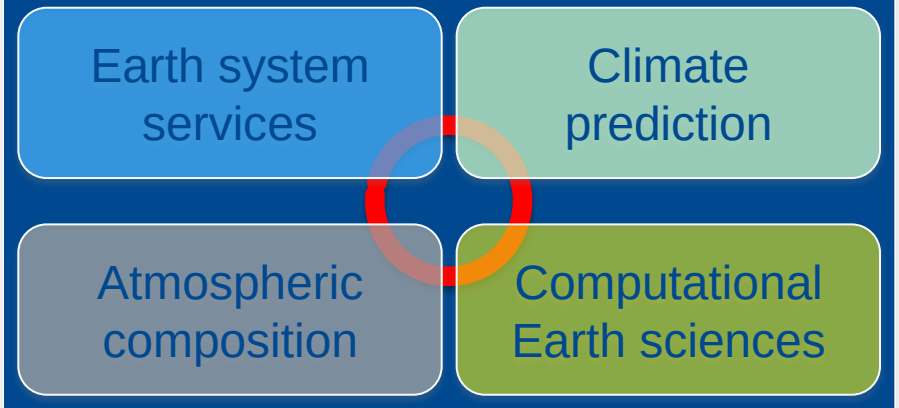
How

Develop a capability to model air quality processes from urban to global and the impacts on weather, health and ecosystems

Implement a climate prediction system for subseasonal-to-decadal climate prediction

Develop user-oriented services that favour both technology transfer and adaptation

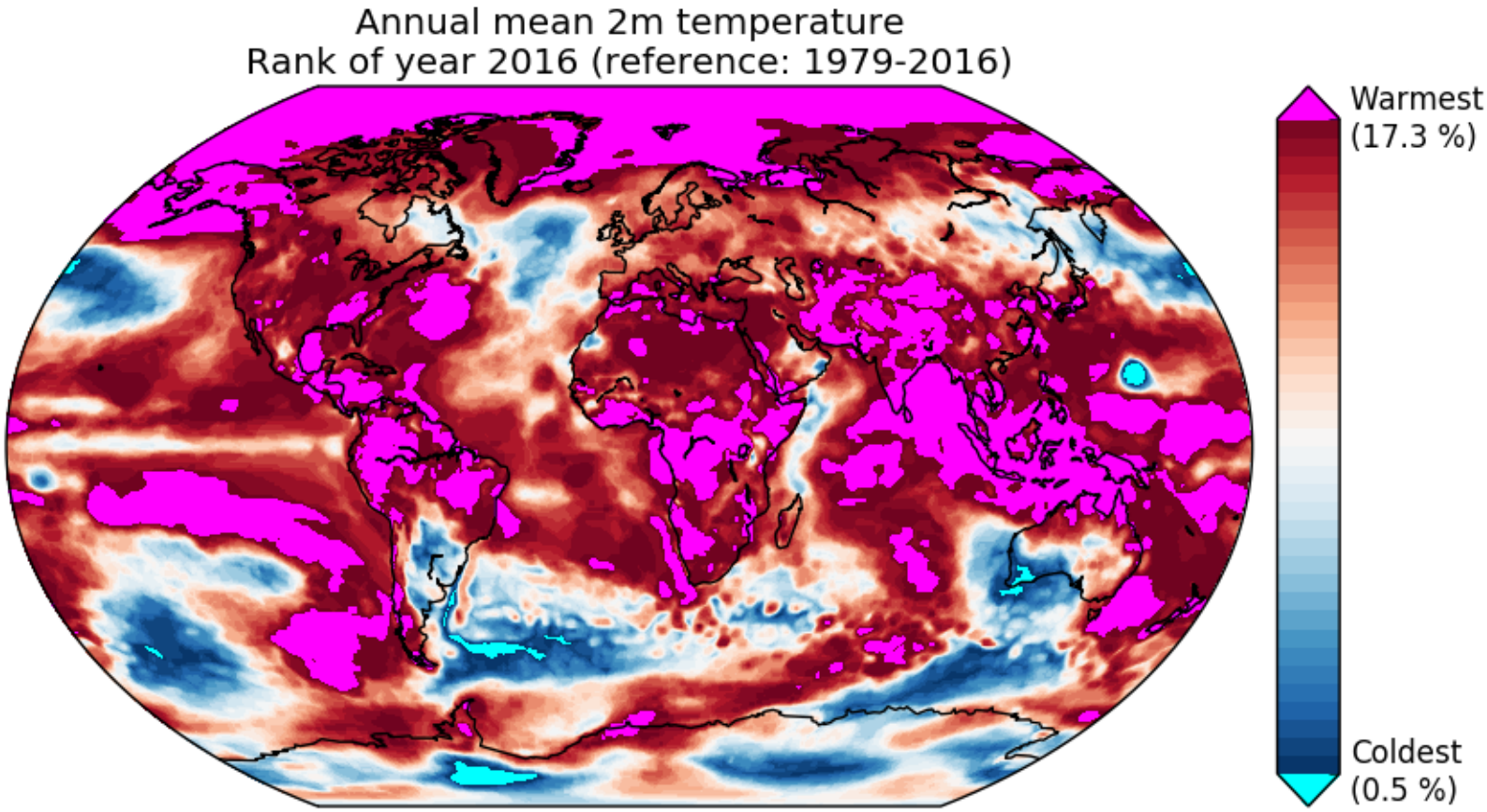
Use cutting-edge HPC and Big Data technologies for the efficiency and user-friendliness of Earth system models



Global climate: What we are after

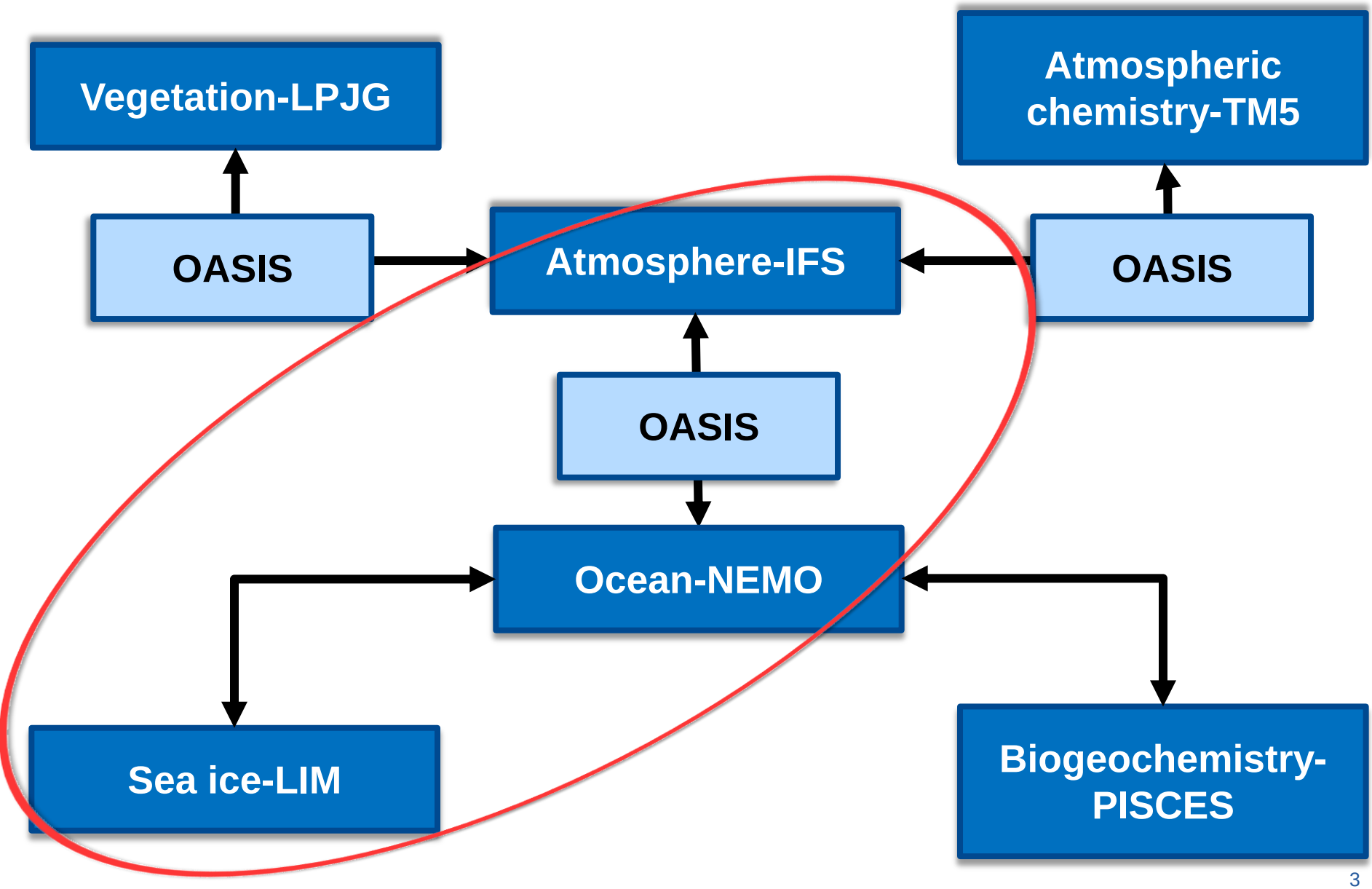
Ranking of the 2016 annual mean temperature over the last 37 years from ERA Interim.

This is an example of the kind of signal that we expect to predict.



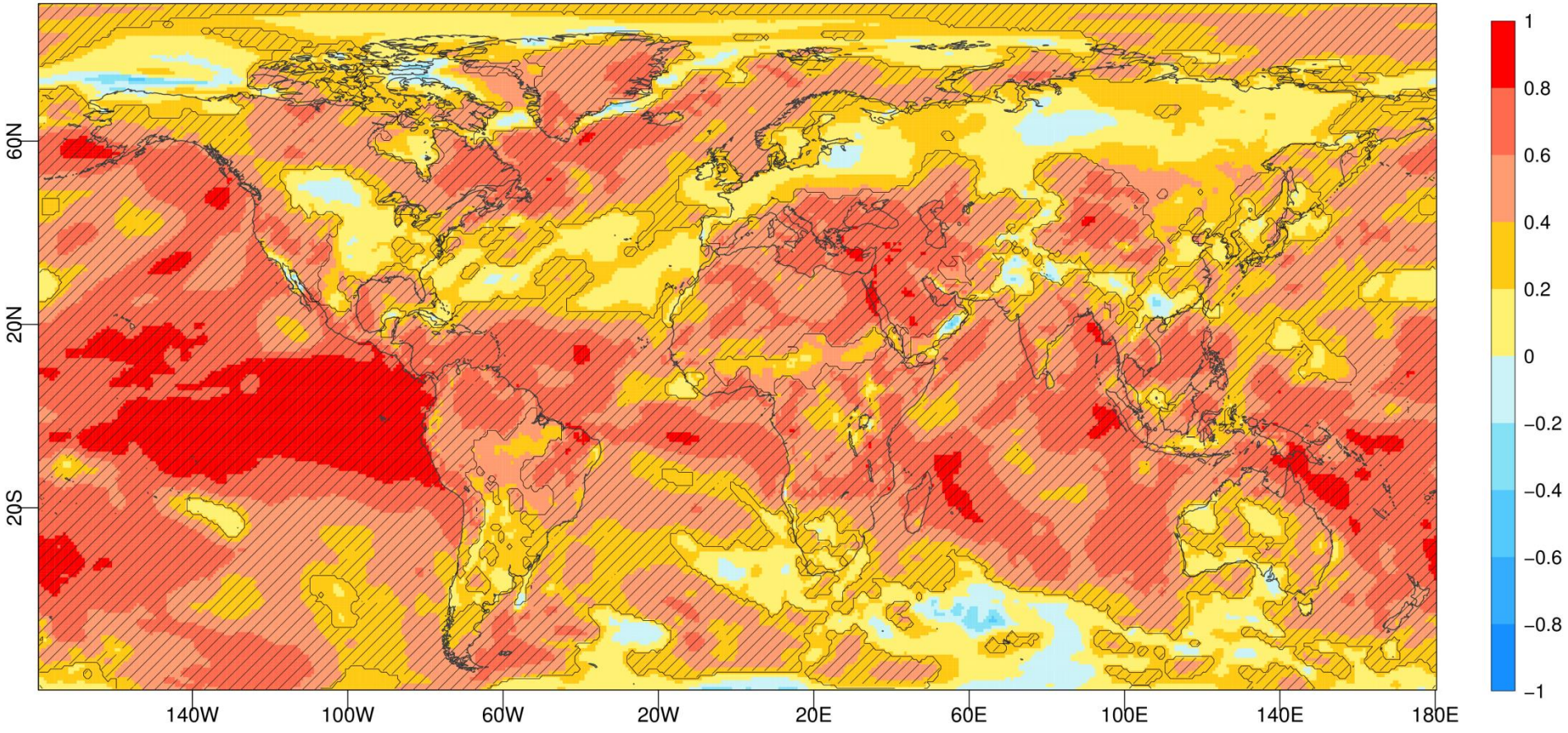
Data: ERA-Interim. Figure: F. Massonnet - BSC

The EC-Earth Earth system model



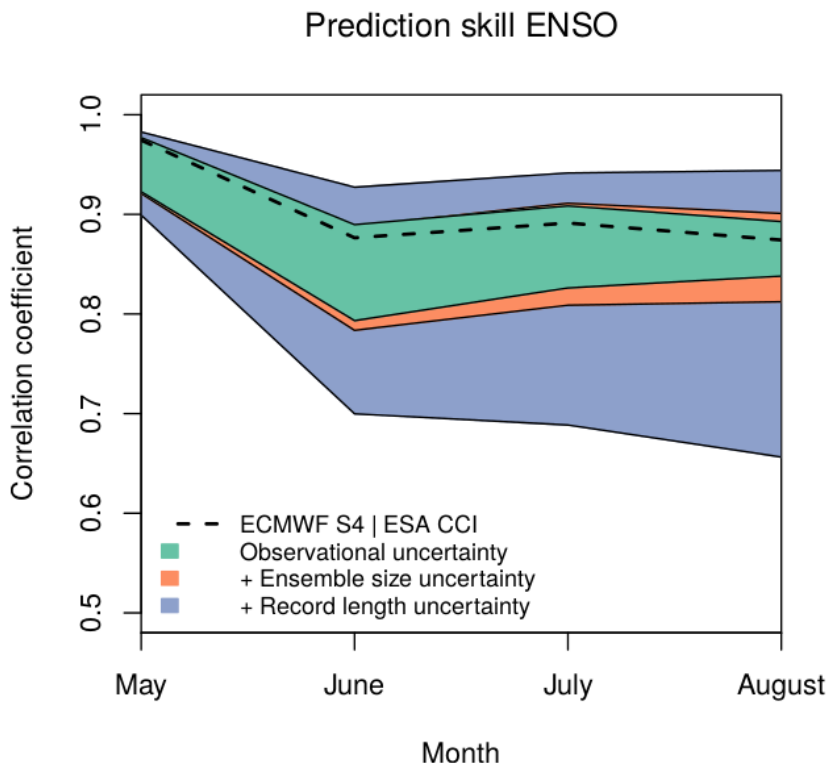
Forecast quality assessment

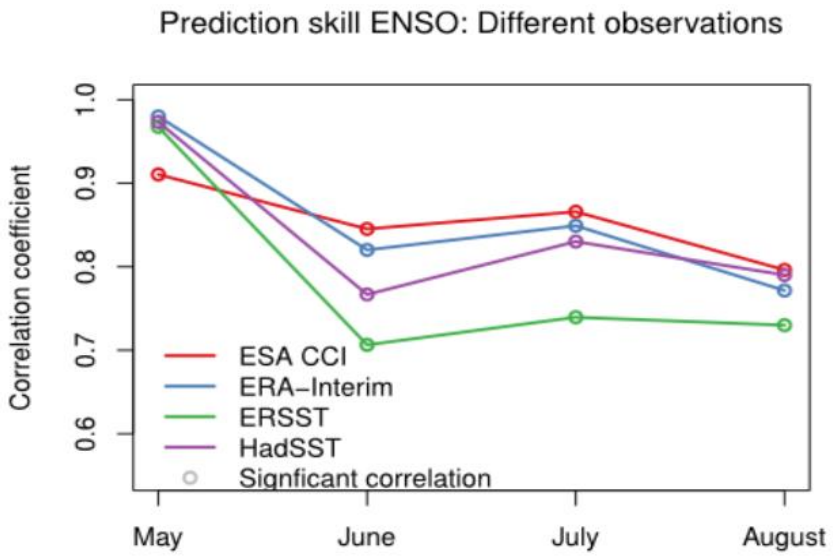
Correlation of the ensemble-mean prediction for the boreal summer (JJA) forecasts initialised on the first of May over 1981-2010. Hatched area for correlations statistically significant at the 95% confidence level.



Sources of skill uncertainty

Niño 3.4 SST correlation of the ensemble mean for (right) EC-Earth3.1 (T511/ORCA025) predictions with ERAInt and GLORYS2v1 ics, and BSC sea-ice reconstruction and (left) ECMWF System 4, both started every May over 1993-2009.





Bellprat et al. (2017, Rem. Sens. Env.)

Model and reference uncertainty

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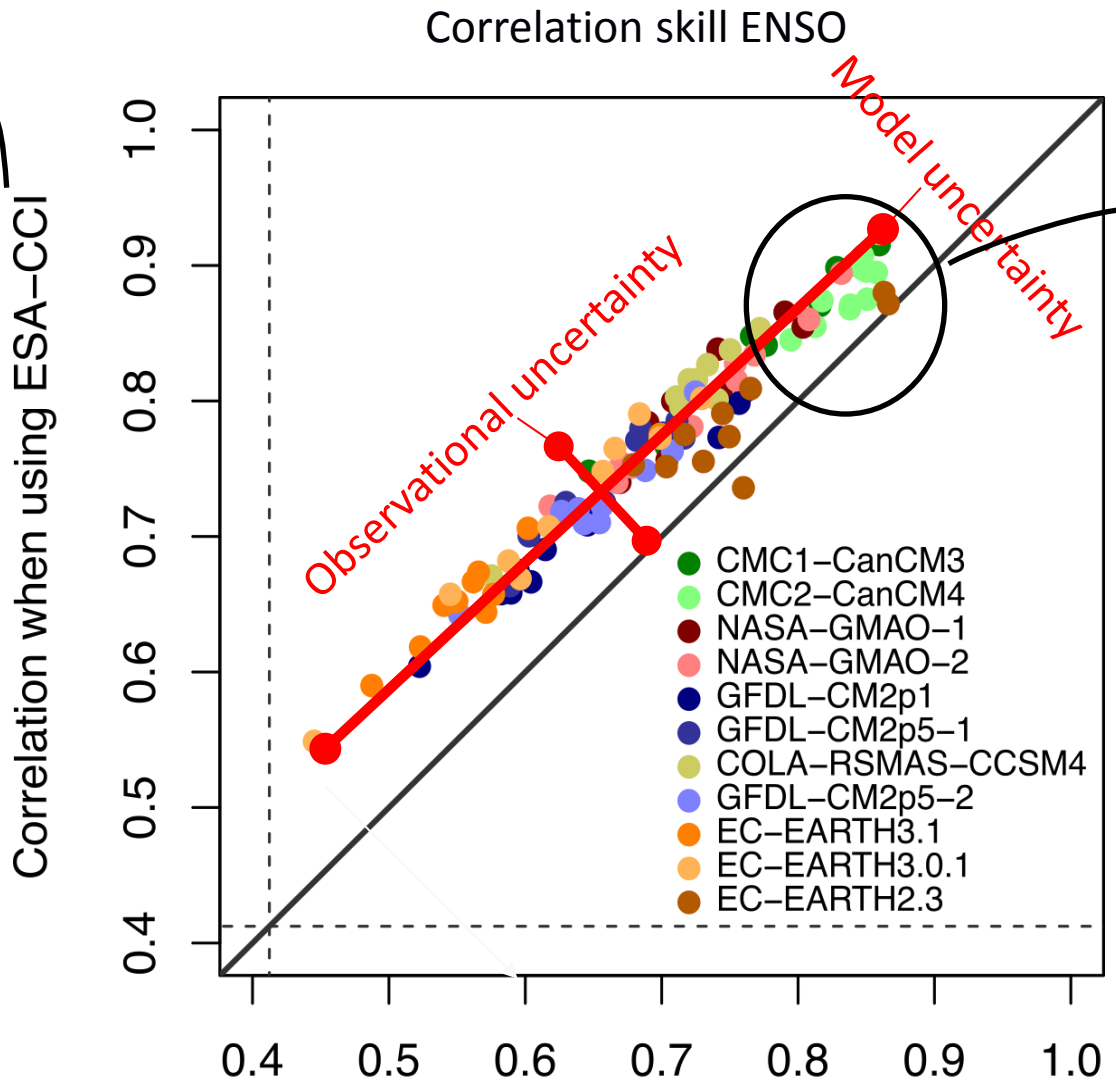
Models can also be used to estimate the quality of observational estimates.

Independent from the models



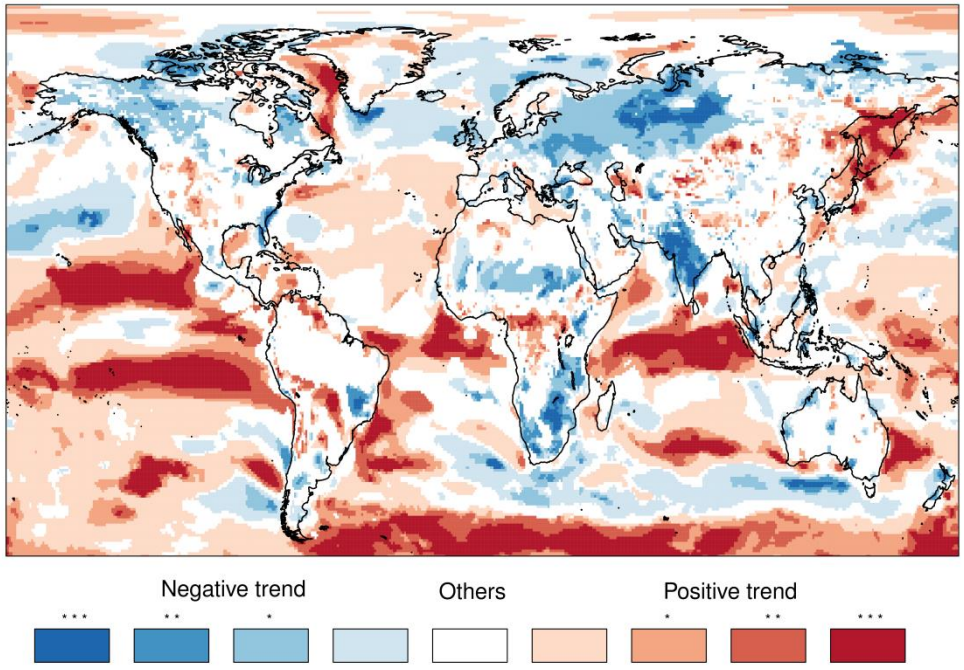
How important for individual systems?

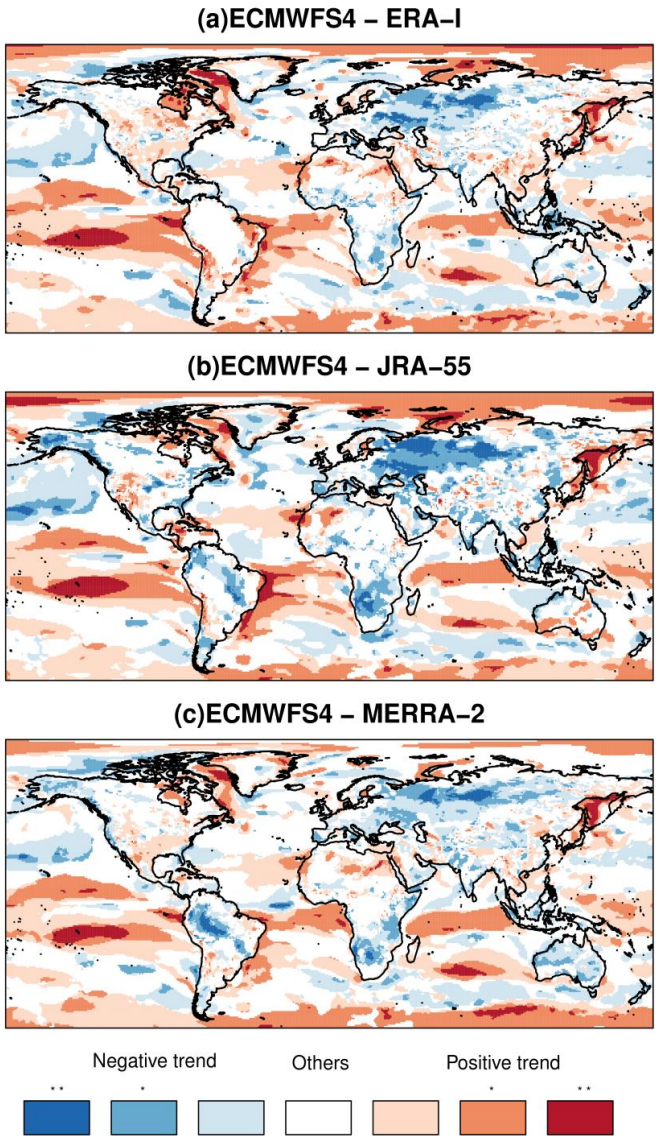
Massonnet et al. (2016, Science)

Reference uncertainty: trends

(Bottom) Coherence of the 10-metre wind speed trends in three reanalyses (ERA-Interim, JRA-55 and MERRA) over 1981-2015 during boreal winter.

(Right) Coherence of the trends between ECMWF S4 and the three reanalyses.





Torralba et al. (2017, ERL)

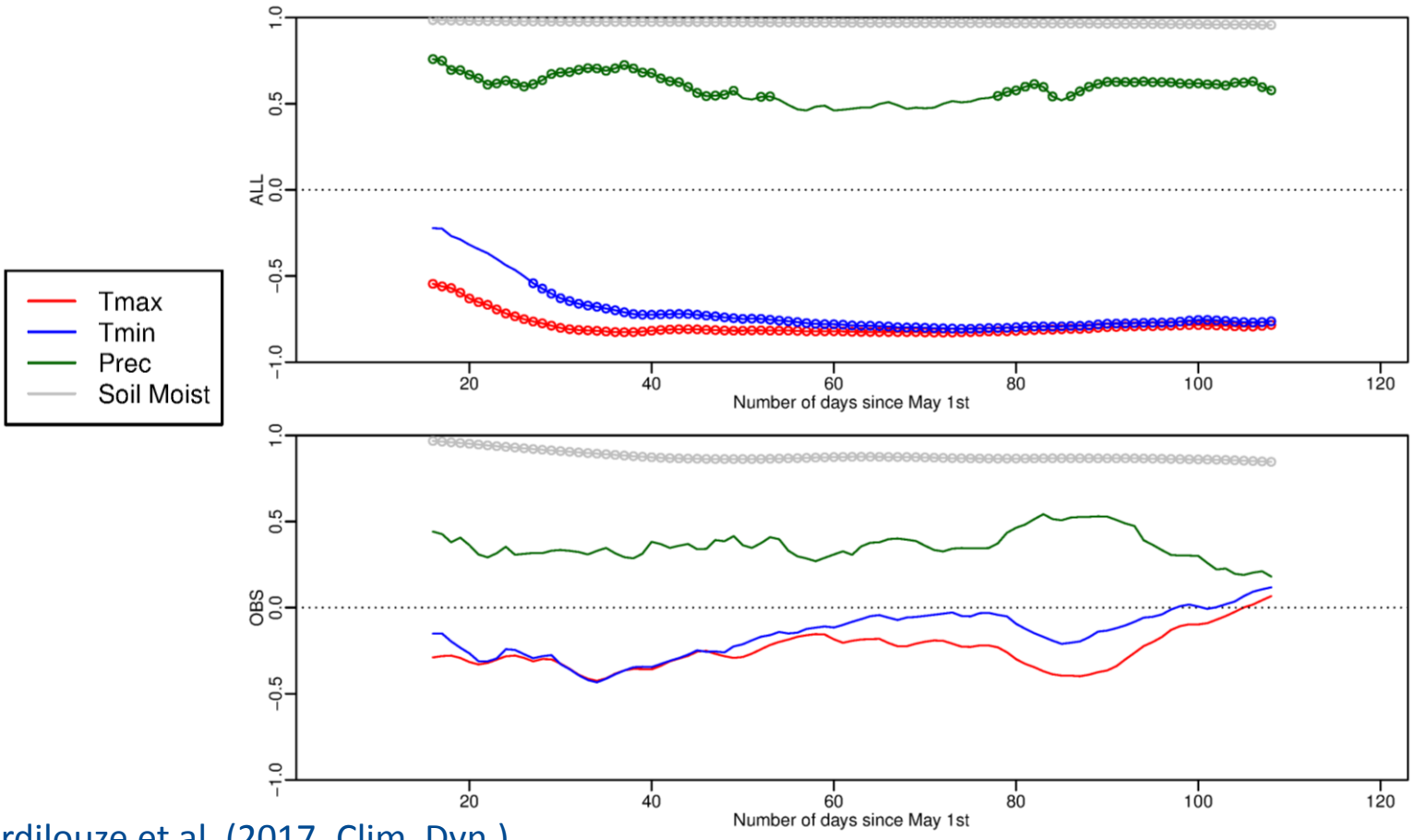
Drift and systematic error

- The previous work is based on forecast and observed anomalies, without full consideration of the climate characteristics.
- Forecast anomalies are computed as differences from a model climatology. Observational reference anomalies use an observational climatology for the same period.
- The model climatology is different for each start date because the model drifts from the initial conditions based on observations towards the model stationary climate.
- In this context, systematic errors are a moving target.
- The characteristics of the drift depend on the variable considered and can be either very fast (SLP, days) or very slow (ocean salinity, decades).
- The stationary systematic errors (those analysed in the CMIP exercises) are not necessarily relevant for climate predictions.

Drift helps uncovering model errors

Correlation between 1st of May total soil water content and 31-day running mean of variables from the SPECS multi-model seasonal forecast (top) and ERAInt (bottom) over North American Great Plains.

The model shifts quickly to excessive land-atmosphere coupling.



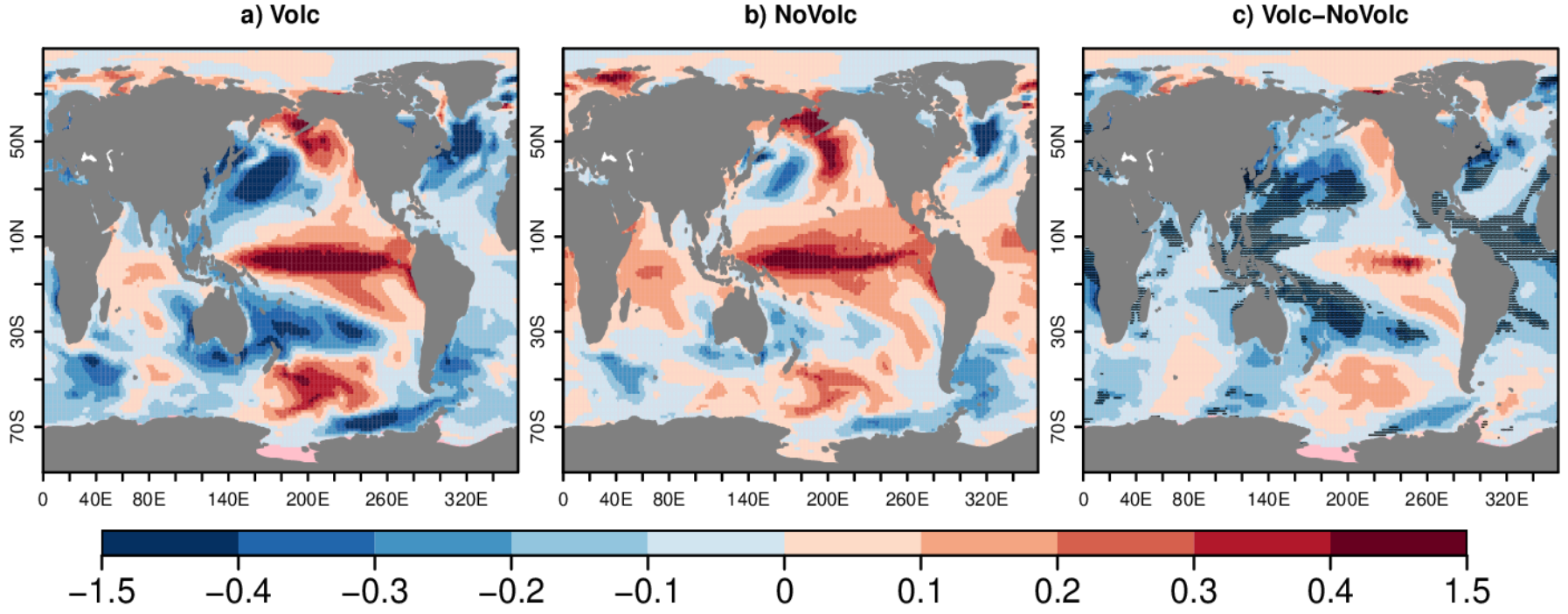
Ardilouze et al. (2017, Clim. Dyn.)

Short-term forcings

- Current climate predictions use CMIP-like forcings (GHG, aerosol, solar irradiance, etc.).
- Model sensitivity to the different forcings is not a trivial problem (link between trends and climate sensitivity).
- However, short-term forcings (aerosols, solar irradiance) need to be estimated somehow during the forecasts because CMIP forcings are either not operational and because forcings can undergo fast variations.
- CMIP6 DCPP and VolMIP are addressing the issue for the volcanic aerosol forcing.

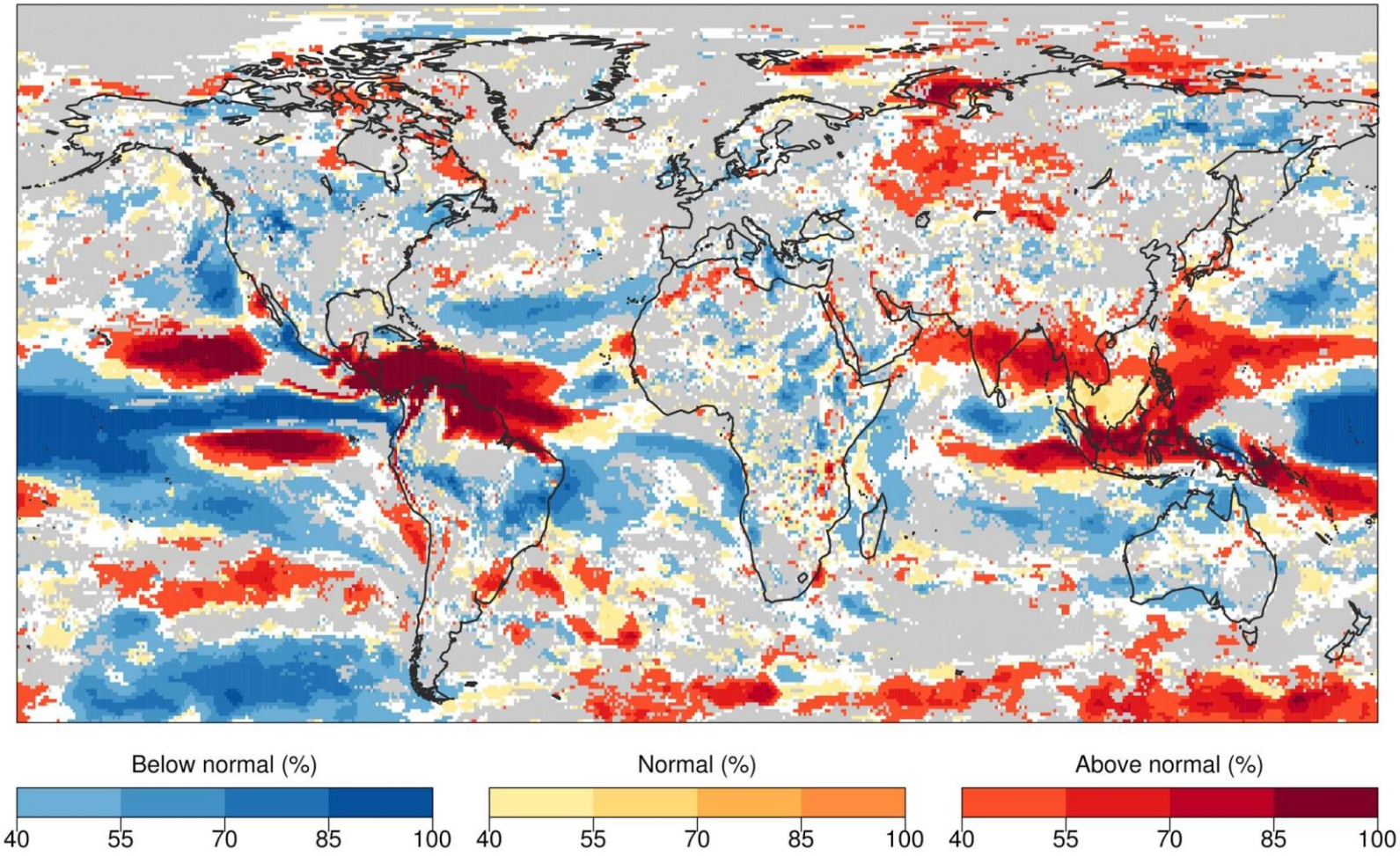
Impact of volcanic aerosol

Mean SST anomaly (K) the first forecast year following the Agung (1963), El Chichon (1982) and Pinatubo (1991) eruptions in EC-Earth2.3 decadal hindcasts a) including the volcanic forcing (Volc), b) not including the volcanic forcing (NoVolc) and c) the difference (Volc-NoVolc). Stipling for differences statistically significant at 95% level.



Ménégoz et al. (2017, Clim. Dyn.)

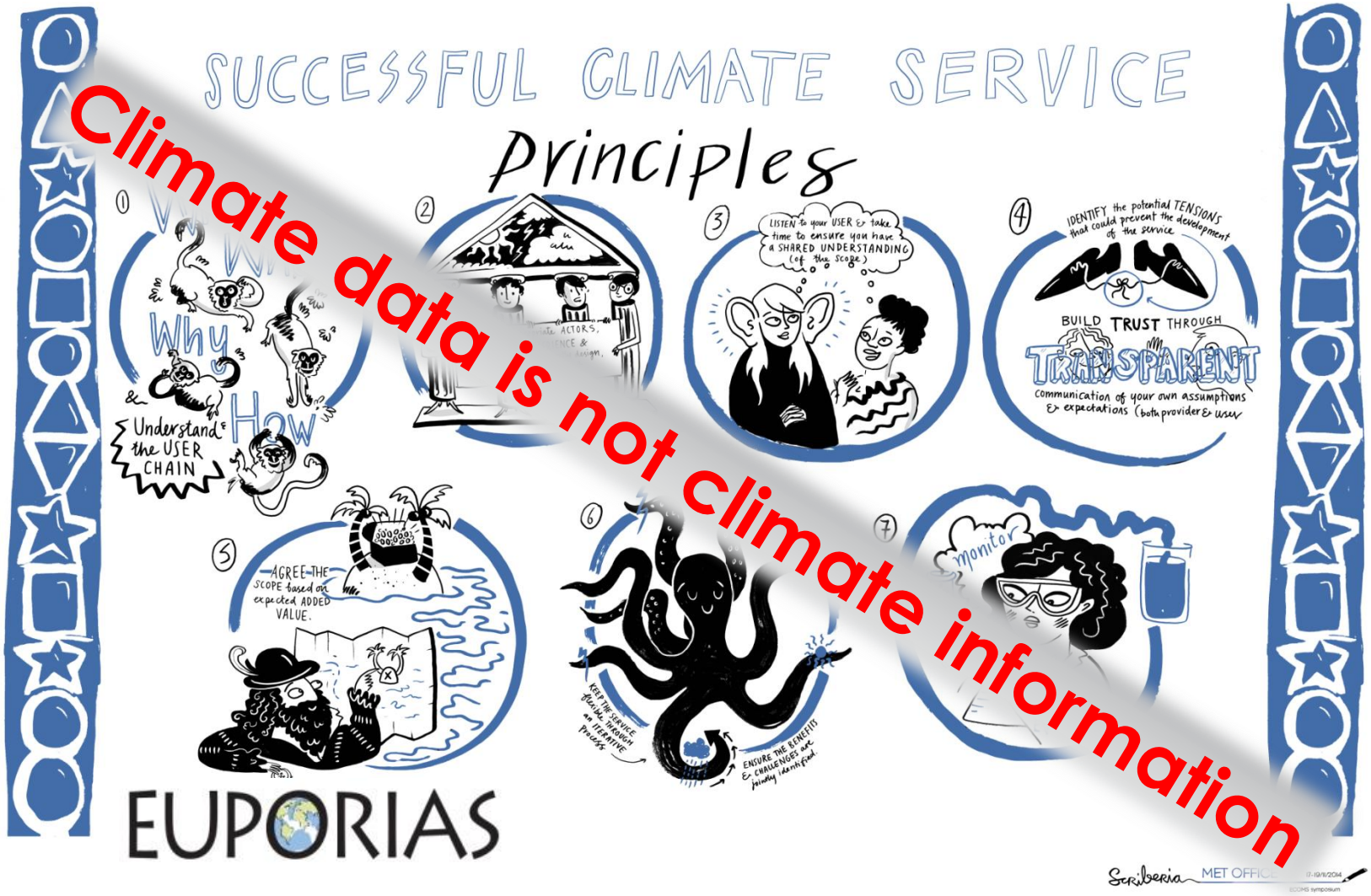
From ensembles to predictions



Wind speed prediction for June 1st - August 31st 2015, issued on May 1st 2005.

The most likely wind power category (below normal, normal or above normal), and its percentage probability to occur is shown. "Normal" represents the average of the past. White areas show where the probability is <40% and approximately equal for all three categories. Grey areas show where the climate prediction model does not improve upon the standard and current approach, which projects past climate data into the future.

Service-driven climate research

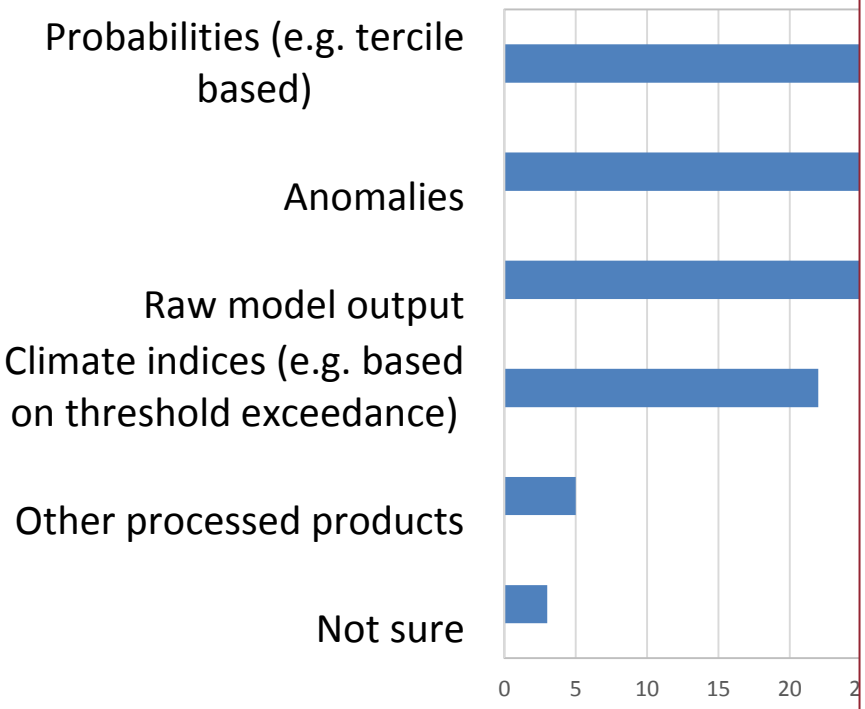


Climate data is not climate information

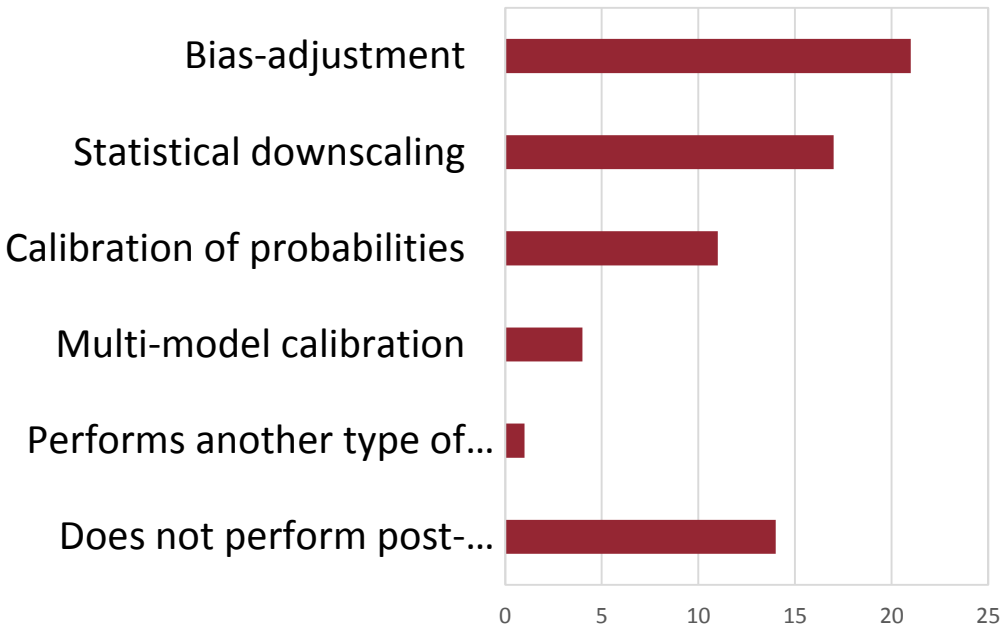
What do the users want?

Results from a user survey performed in the framework of the Copernicus Climate Change Service contract QA4Seas.

"What kind of data from global SF do you use?"

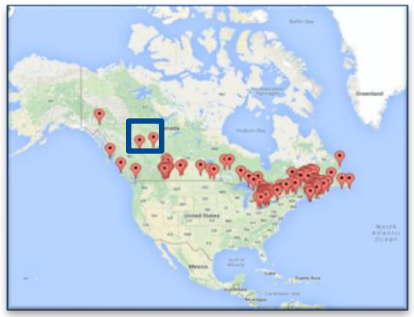


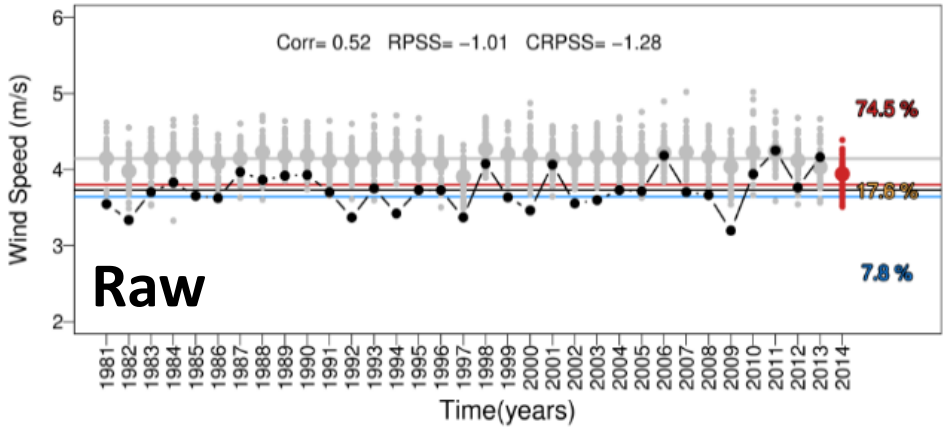
"What type of adjustment post-processing do you perform on the SF data before using it?"



Forecast adjustment

ECMWF S4 10-metre wind speed forecasts for DJF over 1981-2014; reference ERA-Interim.

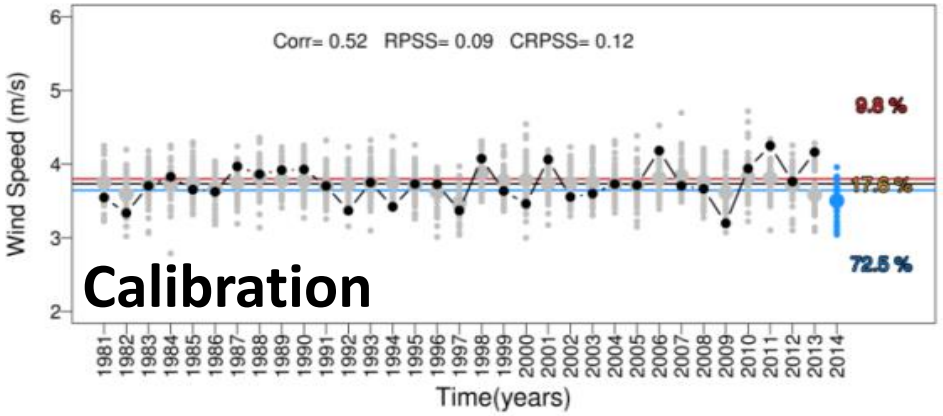


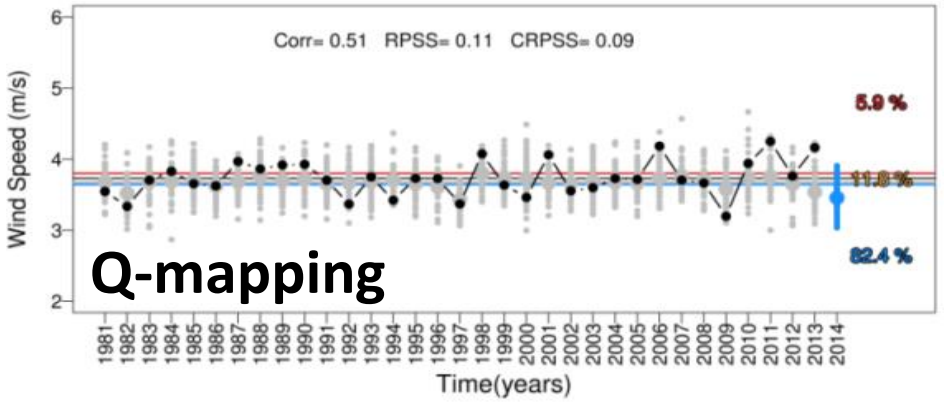


Hindcast mean

⬍ Mean bias

Obs mean



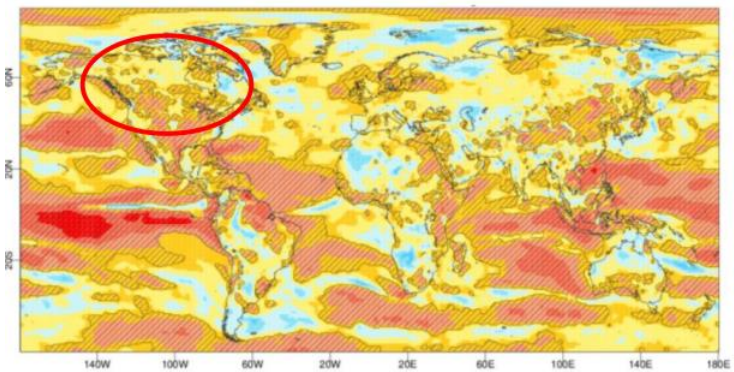


Torralba et al. (2016, JAMC)

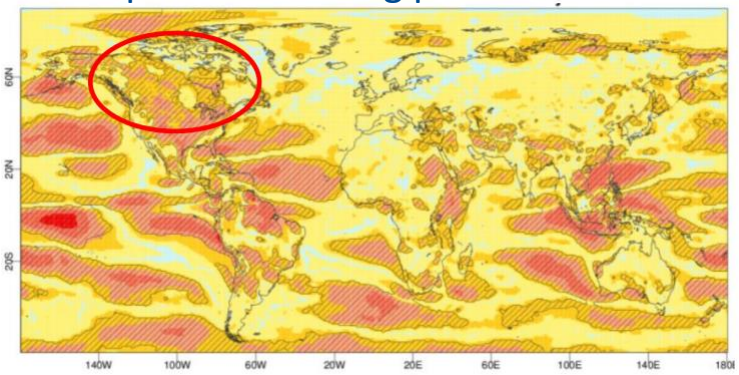
Post-processing: perfect prog

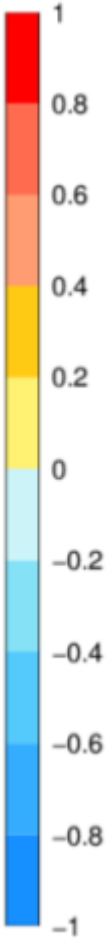
ECMWF S4 10-metre wind speed forecasts for DJF corrected with the predicted Niño3.4 index on a regression estimated using ERA-Interim.

Correlation of the ECMWF S4 ensemble-mean prediction (1981-2015)

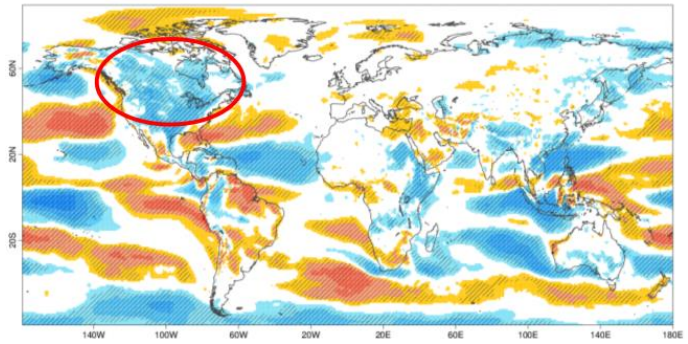


Correlation of the ECMWF S4 ensemble-mean prediction using predicted Niño3.4

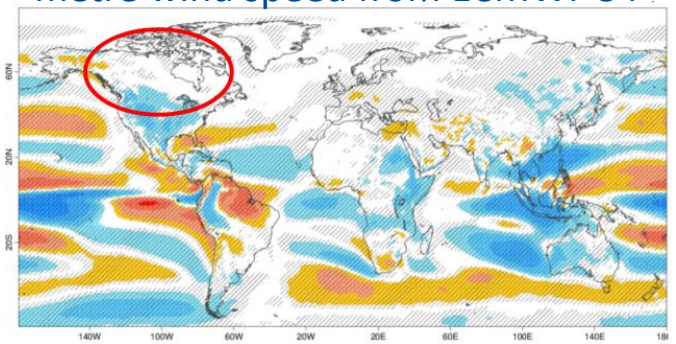


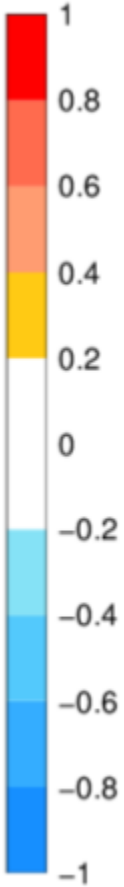


Point correlation of Niño3.4 and 10-metre wind speed from ERA Interim



Point correlation of Niño3.4 and 10-metre wind speed from ECMWF S4





González et al. (in prep.)

Predicting tropical storm frequency

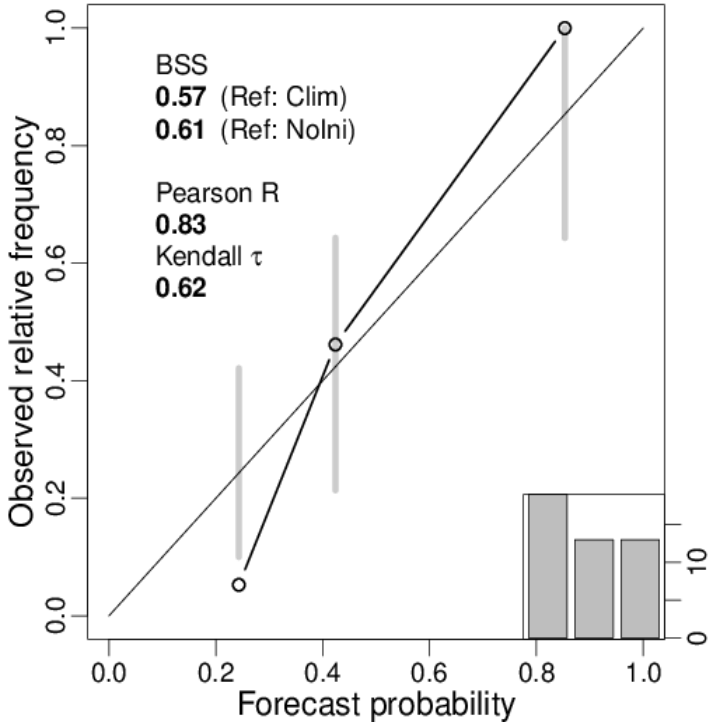
First comprehensive service of predictions of tropical cyclone seasonal frequency

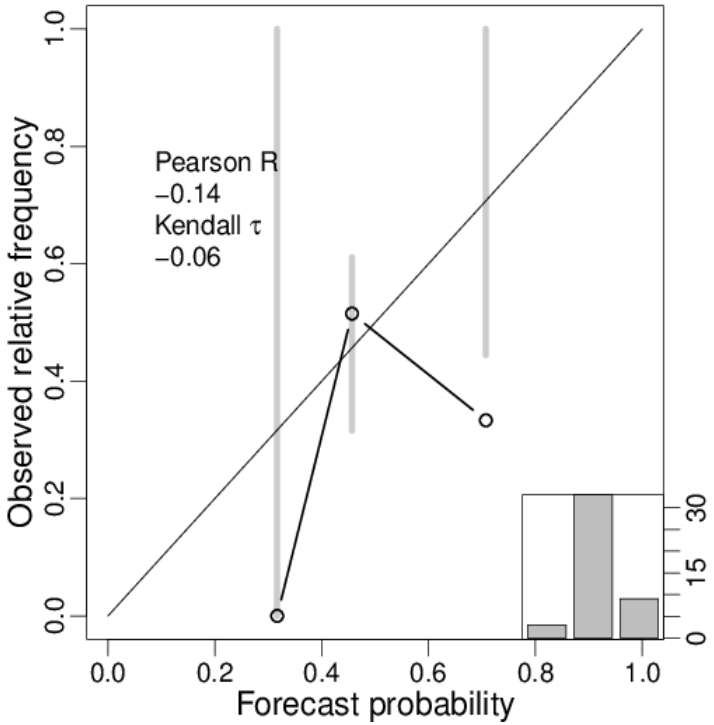
http://www.bsc.es/ESS/seasonalhurricanepredictions/

Predicting tropical storm frequency

Reliability diagrams of (left) initialised and (right) uninitialised MME simulations for basin-wide **accumulated cyclone energy** (ACE). Results are for 2-9 year means above the climatological median from decadal predictions over 1961-2009. Statistically significant values in bold.

Some of the added value of the predictions is their better management of uncertainty, which leads to increased **credibility**.



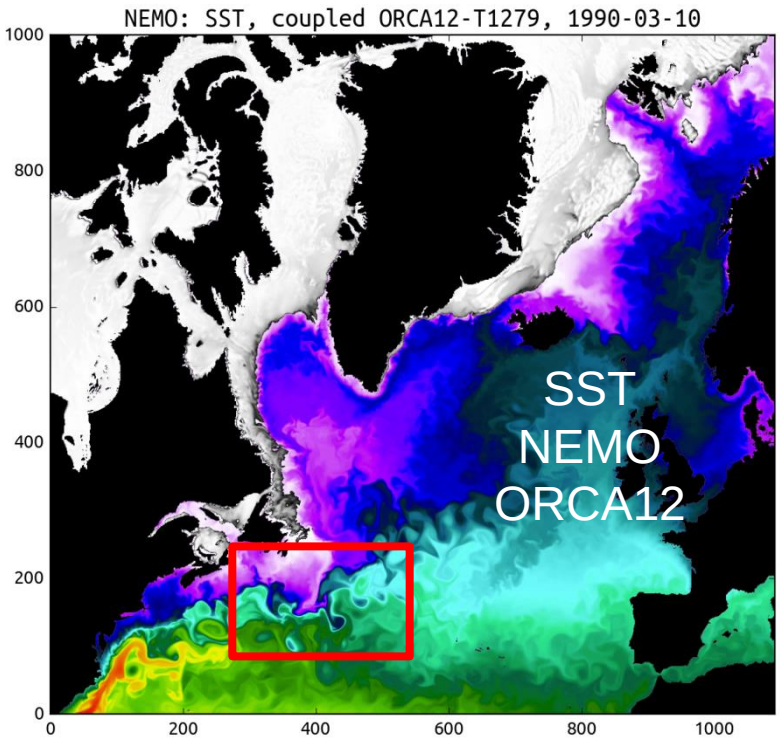


Caron et al. (2015, GRL)

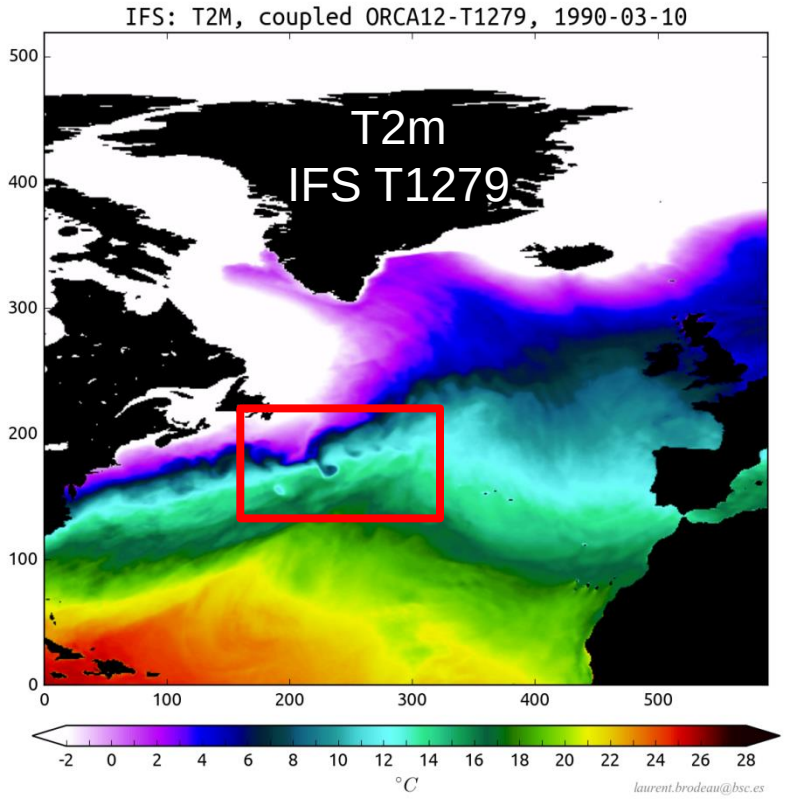
Providing better climate information

- Improve the physical processes in the models.
- Improve the initialisation and illustrate its impact.
- Improve the post-processing.
- Use of multi-model.
- …

High-resolution global modelling

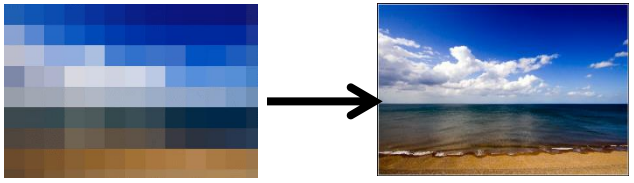


EC-Earth GLOBAL ORCA12-T1279
(ocean and atmosphere at ~10 km)



Effect of increasing the resolution

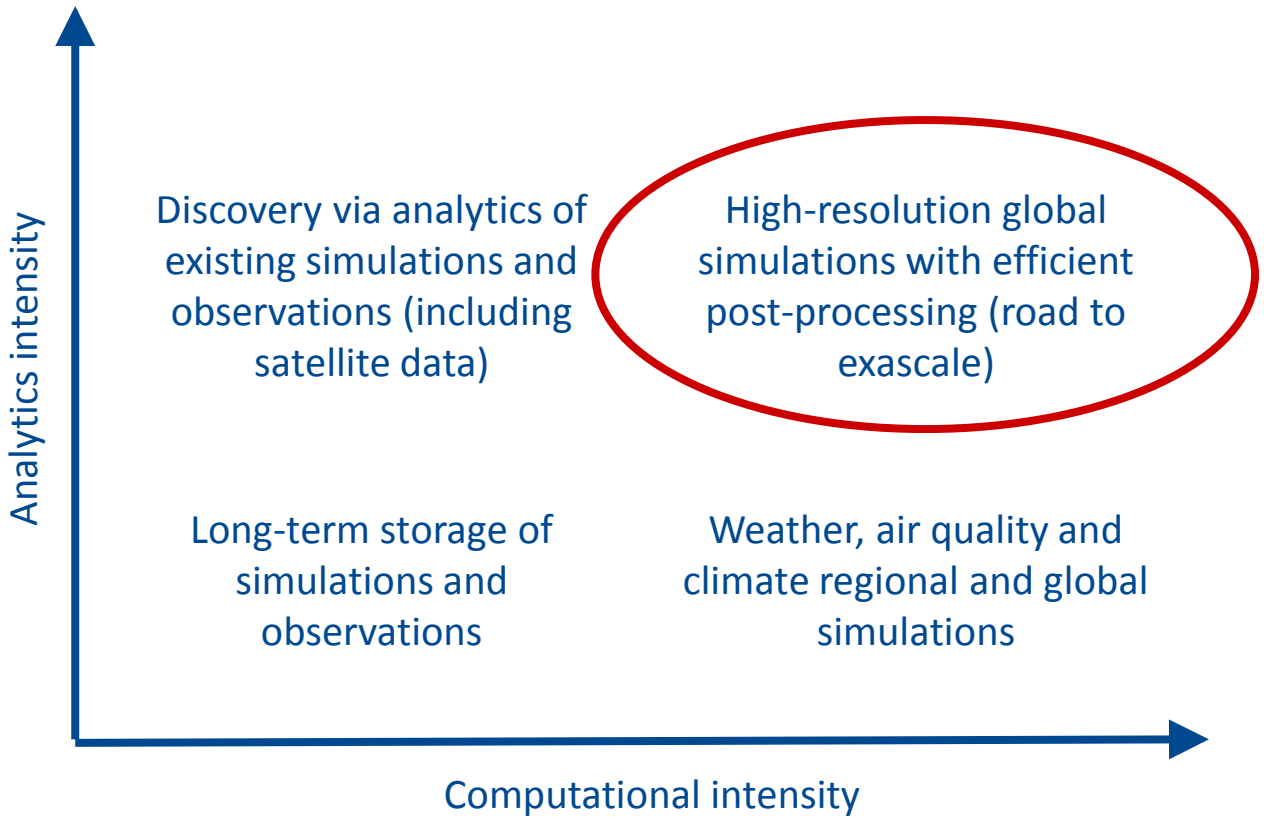
Forecast quality from EC-Earth3.1 seasonal hindcasts (1993-2009, Glorys2v1, ERAInt and ERALand initial conditions). Solid for ES[illegible]CI and dashed for ERSST. Blue for high resolution ocean and atm[illegible]d for high resolution ocean, black for standard resolution.



But this strategy works better after making the models more computationally efficient

Prodhomme et al. (2016, J. Climate)

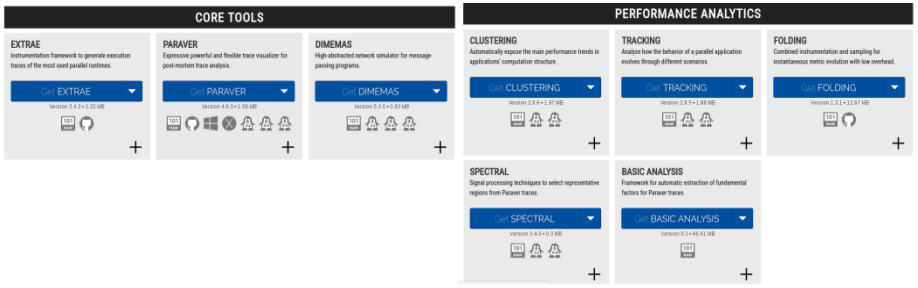
HPC and data analysis



Improving model efficiency

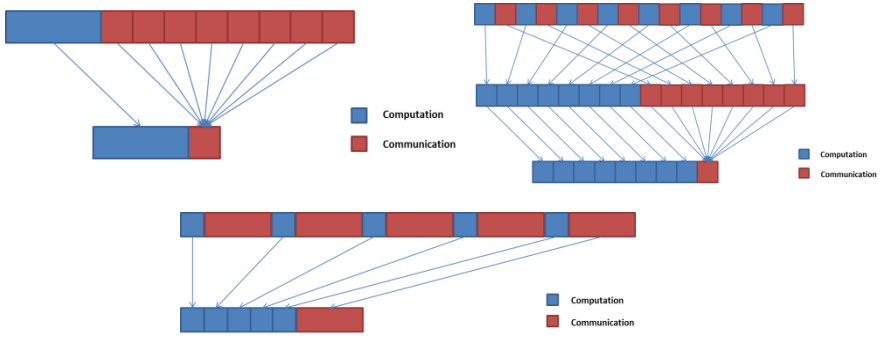
Collaboration with computer sciences department

BSC performance tools



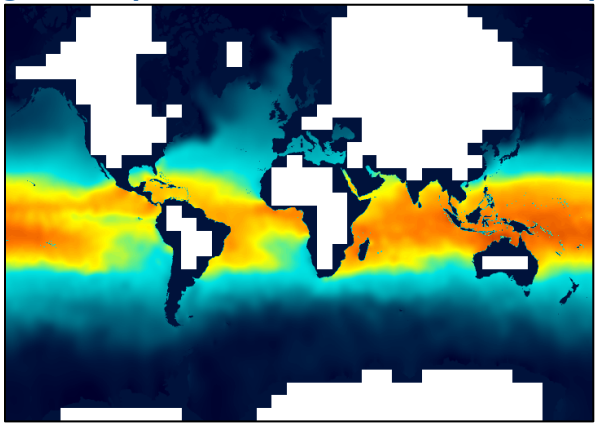
MPI communications optimizations

Reducing p2p and collective communications overhead



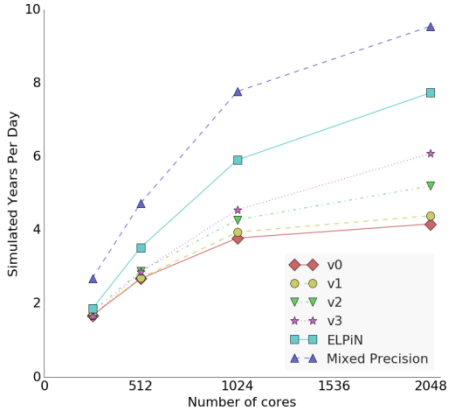
Exclude land processes in NEMO

Finding an optimal domain decomposition



Explore mixed precision

Which precision is needed in NEMO?



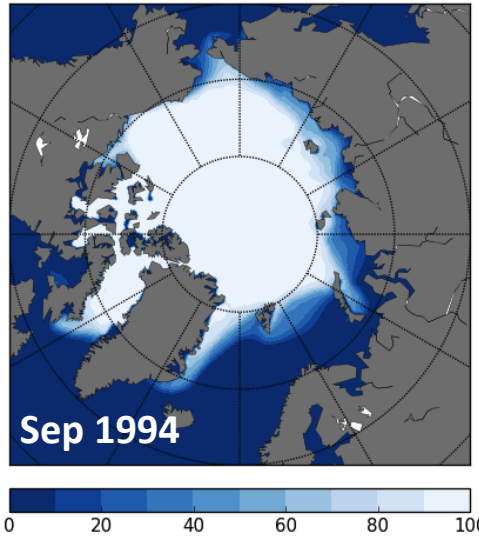
Potential overall improvement:

2x

M. Castrillo, O. Tintó, M. Acosta, K. Serradell

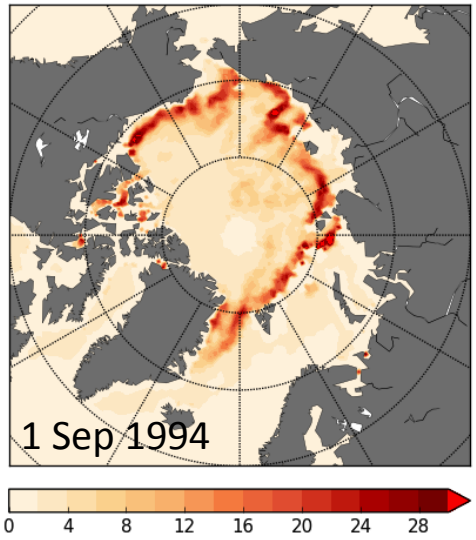
Better sea-ice initial conditions

25-member EnKF analysis (one-month window) with EC-Earth3.2 where ESA-CCI concentration data are assimilated.

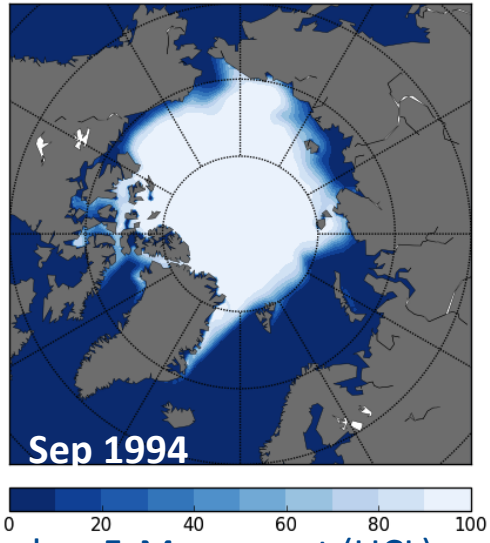


Free-running
EC-Earth3.2

Ensemble mean SIC

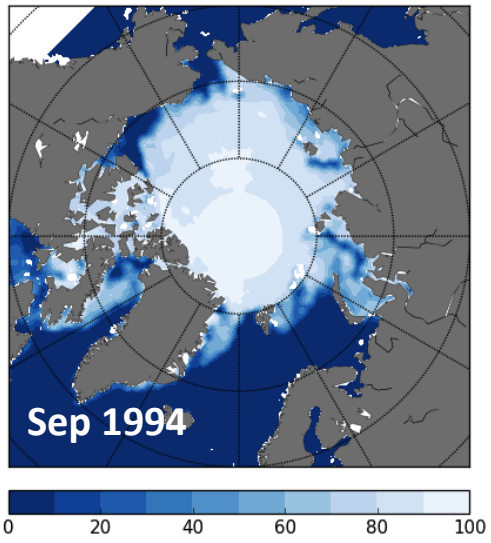


ESA CCI SIC uncertainty



EnKF (SIC)
EC-Earth3.2

Ensemble mean SIC

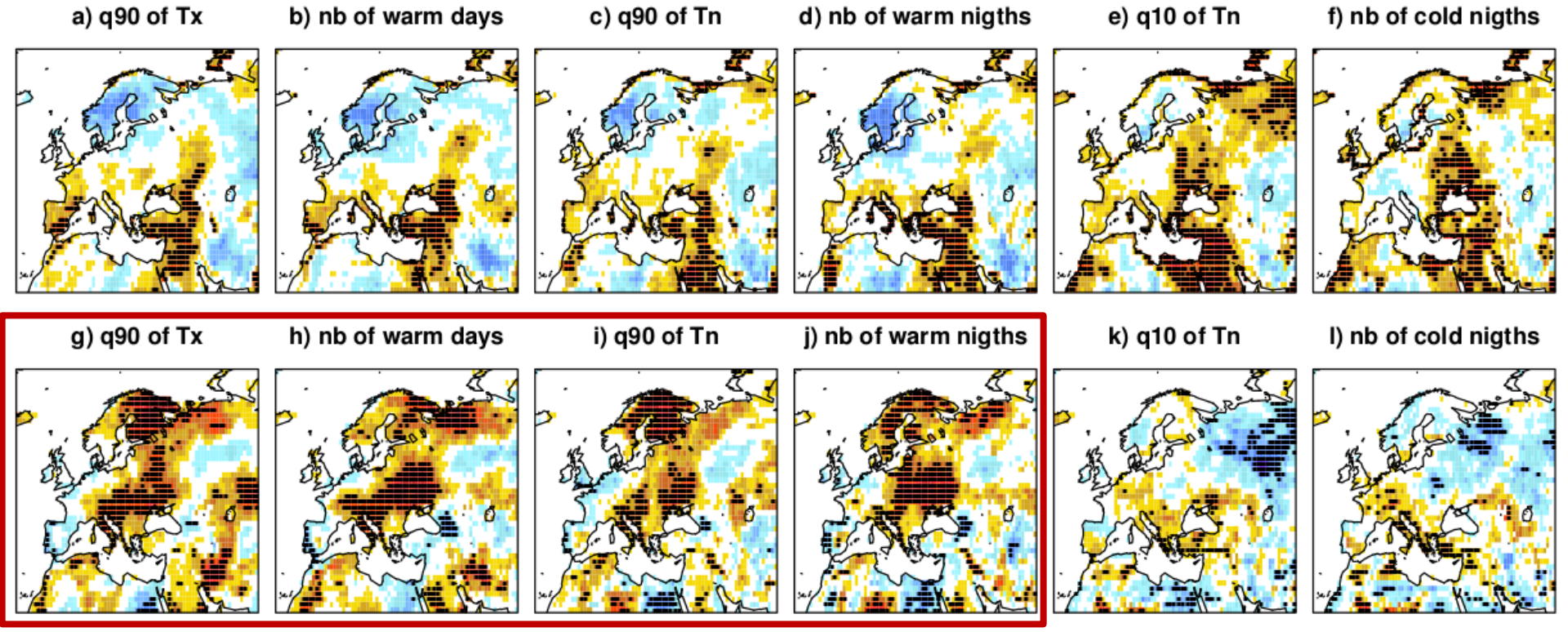


NSIDC SIC

N. Fuckar, F. Massonnet (UCL)

Better land-surface initial conditions

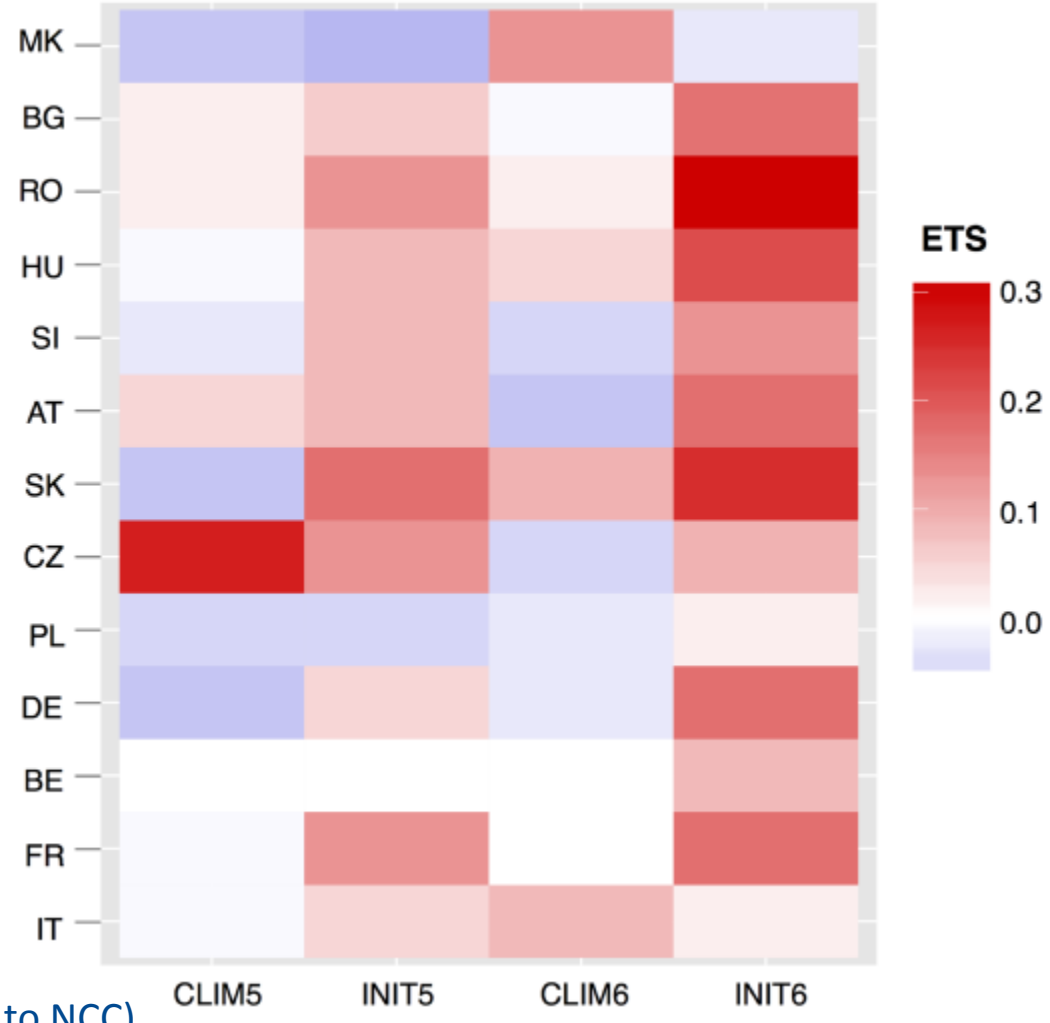
JJA near-surface temperature correlation of the ensemble mean from experiments with a climatological (top) and difference with one with realistic (bottom) land-surface initialisation. Results for EC-Earth2.3 started in May over 1979-2010.



Prodhomme et al. (2015, Clim. Dyn.)

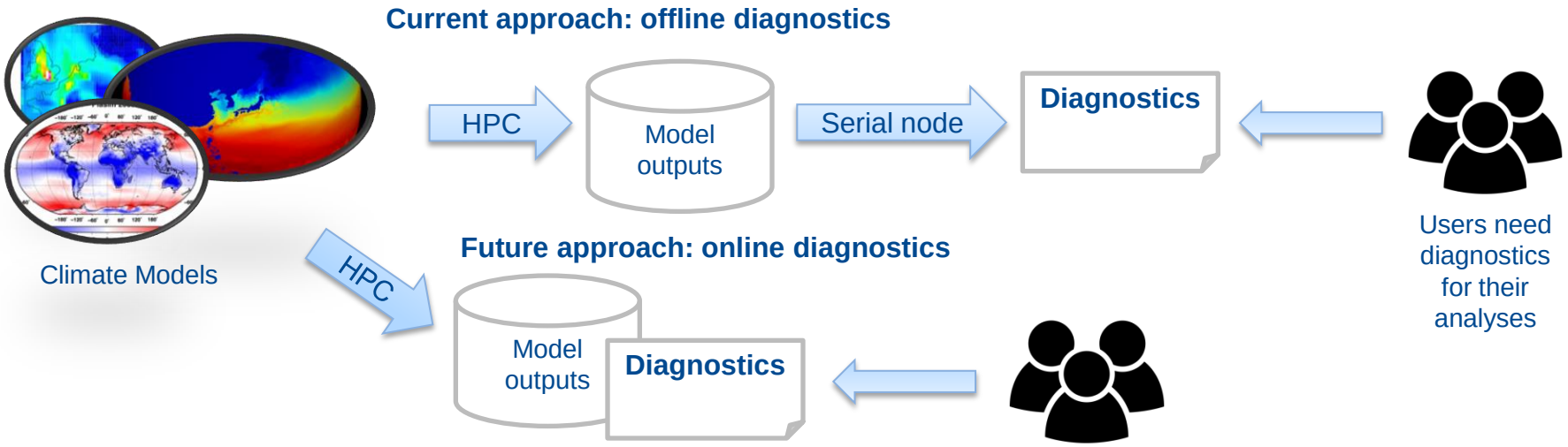
Climate information: agriculture

Equitable threat score (ETS) of predictions of poor maize yield (lower quartile) from EC-Earth seasonal predictions when land-surface is initialised with realistic initial conditions (INIT) wrt no information (CLIM).



Ceglar et al. (submitted to NCC)

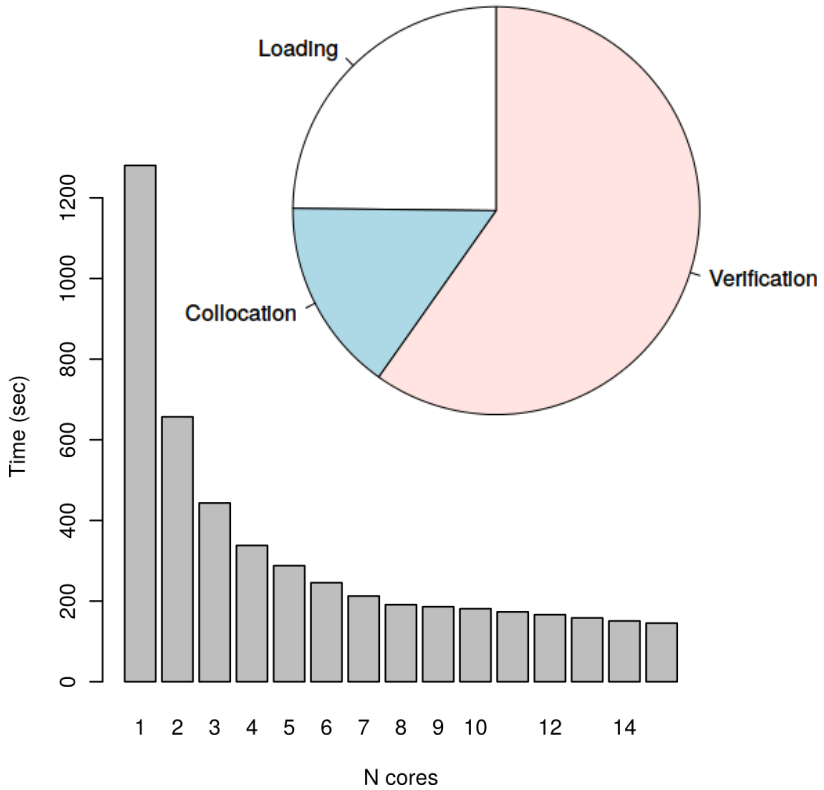
Improving diagnostics efficiency

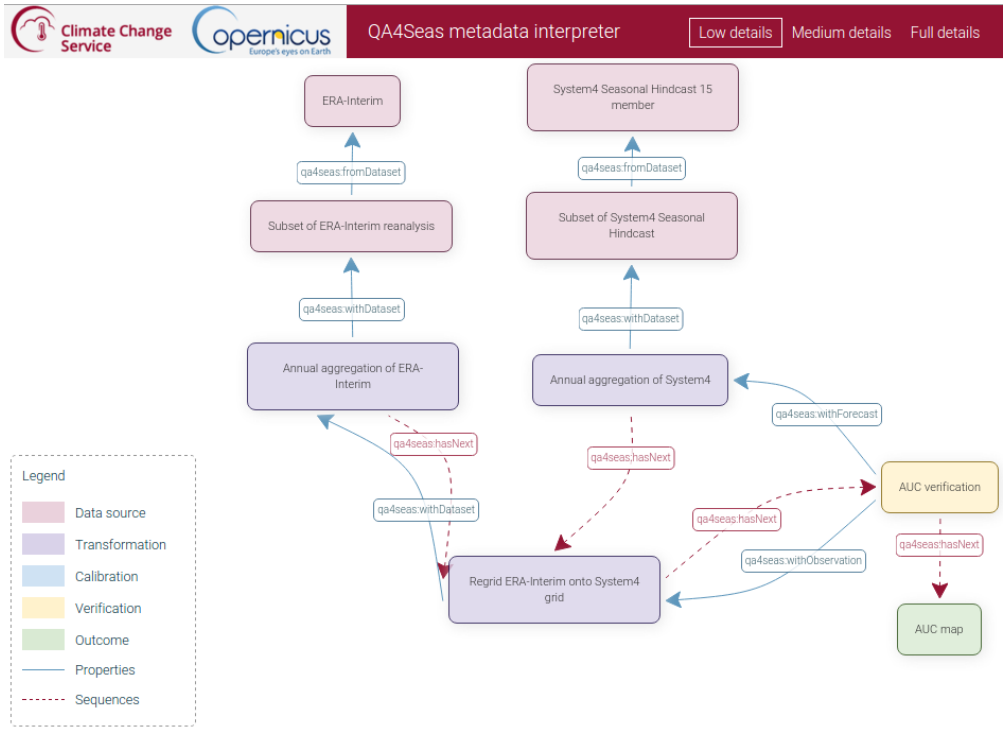


- Diagnostics computed as Analytics as a Service
  - Diagnostics online (during model run)
  - Reduced data traffic
  - Diagnostics possible on the computing nodes (using GPUs)
  - New diagnostics (data mining of extremes) possible
  - The user gets the results faster → crucial to adapt to climate change and to develop climate services (public and private)

Improving diagnostics efficiency

- **Computing performance is key**: (left) scalability of a ROC area estimate using loadeR, SpecsVerification and easyVerification.
- An RDF-based approach aiming at the reproducibility of objects (NetCDF file, image) with human and machine-readable solution using a semantic metadata model has been created in QA4Seas.





Symbiosis: research and services

A new paradigm has come to stay: user-driven research

- **Progress**: opportunities appear in a context where research and services grow closer together.
- **Heterogeneity**: link to and merge our data with communities with larger impact (urban, arts, social).
- **Education**: in the era of open data, take advantage of the open education opportunities.
- **Standards**: in a collaborative environment standards are a must and everyone's (users and providers) responsibility.
- **Technology**: make the most of a rapidly evolving technology (heterogeneous nodes, software, mobile data capture, visualisation, storage/compression, computing and storage outsourcing).
- **Industry engagement**: involved the private sector in improving systems to make them more efficient